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# Solar Irradiation Prediction using back Propagation and Artificial Neural Network

**Harendra Kumar Verma[1], Ashish Bhargava[2]**

[1]Research Scholar, [2]Professor,
[1,2]Bhabha Engineering Research Institute, Bhopal, Madhya Pradesh, India

**ABSTRACT**

Solar Energy is one of most promising potential renewable sources of energy. But among all the conventional sources of renewable energy, its nature is quite unpredictable owing to the fact that the solar irradiation keeps on changing and fluctuating. This leads to uncertainty in ascertaining the exact measure of solar power that can be harnessed. Hence forth, a solar irradiation model based on solar irradiation using ANN shall aid in preliminary estimation of the measure of solar power energy that is available for usage incorporating the load dispatch and grid. This proposed work of study puts forward an Artificial Intelligence based model of a Solar Irradiation Forecasting implemented by Artificial Neural Networks (ANN). ANN is utilized accredited to its adaptive, data driven and nonlinear nature that exhibits high efficacy in forecasting domains. An endeavor has been also made for solar irradiation forecast using the ANN along with Levenberg Marquardt (LM) algorithm. The primary reason for using the Levenberg Marquardt algorithm is the fact that is an extremely effective algorithm employing back propagation. The attributes of the algorithm are high stability and speed which yields lesser number of iterations and relatively less magnitude of errors.

The evaluation of the proposed system needs to be done on performance specific parameters which in this case are chosen as Mean Absolute Percentage Error (MAPE) and Regression. Mean absolute percentage error indicates the amount of errors present in the prediction which is to say the deviation between the actual targets and predicted output. Another parameter which validates the mean absolute percentage error is the regression which is a graphical representation of discrete values in the target set and the predicted output. Additional analysis mechanisms such as training states has been also presented which depicts how the mean square error plummets as the number of iterations increase. The variation of mean square error can be seen in training, testing and validation phases. The neural network topology used is 1-20-1 indicating one neuron in the input layer, 20 neurons in the hidden layer and 1 neuron in the output layer respectively. It has been shown that the proposed methodology attains a very good accuracy of approximately 97.74% with the error rate amounting to a meager 2.76%. This model serves to be a robust mechanism and shows good performance. The low error and high accuracy can be attributed to the efficacy of back propagation in Artificial Neural Networks. A comparative analysis is also presented with contemporary work that attains an error of 30%, proving the fact that the proposed system outperforms the contemporary techniques.

***KEYWORDS***: *Renewable energy; artificial neural network; artificial intelligence; survey*

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## 1. INTRODUCTION

Solar power is one of the most reliable renewable sources of energy and holds strong potential for harnessing energy from it. If used in an effective method, it can aid in meeting high energy requirements in today high energy demanding economy. But one of the flipsides to the solar power energy is its uncertainty of the measure of energy that can be actually obtained. Among all the renewable resources of energy, like wind energy, geo thermal energy and tidal energy, the energy from solar power is subjected to the most fluctuations and variations as the solar irradiation keeps on changing and varying with time owing to various reasons related to natural phenomenon. This causes the amount of energy that can be harnessed at a given time asnon determinable. If this unsure system is utilized to harness the energy of solar power, it can render to be very infeasible and inappropriate in terms of power quality, system stability, power frequency and other voltage and power related issues may arise. The fluctuations and varying solar irradiance may subject the system to unstable results. The grid power, load dispatch would also get impacted.

Therefore to solve this problem and make solar irradiation energy harnessing a reliable resource, the concept of solar irradiation forecasting plays a crucial role. The initial forecasting of solar irradiation shall resolve this for a good and proper solar power generation for the grid system. As the measure of solar irradiation power depends on the mean daily solar irradiance, solar irradiation forecasting methodology shall aid us in attaining our objective efficiently.

A number of diverse and broad ranges of concepts can utilized in this regard to forecast solar irradiation power. These methods are categorized according to their groups as in whether they are physical or statistical in nature of approach of forecasting. The conventional methods are employed are mainly based on numerical weather prediction method where it is taken as the input for the forecast. But today the efficiency of Artificial Neuron Networks is undisputable. ANN possesses high capability to figure out non linear relations and connections among the input output domains. So in this proposed work, Artificial Neural Networks has been chosen as the most effective method for the solar irradiation forecasting. It has been implemented in the MATLAB environment.

This proposed study of work very clearly shows and illustrates the solar irradiation forecasting model and its analysis and study based on the ANN with three distinct algorithms implemented. Endeavour has been made to forecast the wind speed using ANN along with Levenberg-Marquard (LM) algorithm. The results have been assesses according to the convergence speed relating to the Mean Absolute Error (MAE), Mean Square Error (MSE) and Mean Absolute Error (MAPE).

## 2. Literature Review:

Literature Survey outlines the past research works that have been carried in this context of work. These are essential as they give an over view about the past works done and problems that have been resolved and the areas that have scope for future improvement.

L.SaadSaoud et al. in 2016 [1] put forth a technique to design a wavelet neural network for the prediction of solar irradiation. In the paper, a fully complex valued wavelet neural network was designed wherein the Neural Network architecture's mechanism was such that the activation function could compute the wavelet transform of the previous data once the neural network was trained by the training data. Moreover it was shown that the system used fully complex values of weights pertaining to the wavelet co-efficients which would affect the weight while training the neural network architecture. It was shown that the proposed technique was able to achieve an accuracy of around 94.8%. Vishal Sharma et al. in 2016 [3] presented an idea of using solar irradiance prediction to gauge the output of solar PV systems. The technique used a mixed wavelet neural network for the prediction of solar irradiance prediction. The proposed system utilized the inherent signal compression property of the wavelet transform to predict data which was highly non- stationary with a lot of information content because of the randomness of the data set. The design used a Morlet-Mexican hat wavelet function as the activation function of the designed neural network. The mean square error for one hour prediction was 17.82%, thus an accuracy of 82.18%. TarlochanKaur in 2016 [6] gave a research that consisted development of five different ANN models for short-term wind speed forecasting. In this work of study, they employed train BR and train LM algorithm for the training purposes. These 5 different approaches were used to bring the best performance metric out of each one of them. These models varied on the basis of number of neurons and number of iterations. Following the training it was found that the optimal metric for the configuration was of 4 input neurons, 19 hidden layer neurons and 1 output layer neuron. As there was no data pre processing implemented, the system exhibited 70% accuracy with 30% error metrics. M. Rajendra et al. in 2015 [14] discuss the numerical simulation of the multiple crack identification of a cantilever beam with zero noise and with 5% Gaussian random noise addition to the input patterns was evaluated with ICRBF neural network in comparison with IRBF, CRBF and RBF neural networks in frequency domain. LHS technique was used to sample the different levels of crack depth and their location as output patterns in the designed search space; and FFCs and DSIs as input patterns were simulated numerically from finite element analysis (FEA) to train the neural networks.M. Sivachitra et al. in 2015 [15] developed meta-cognitive fully complex-valued functional link network (Mc-FCFLN) for solving real valued classi-fication problems has been presented. The Mc-FCFLN is a network without hidden layers. The neurons in the input layer ofMc-FCFLN employ a polynomial expansion for introducing the nonlinearity. Moreover, the neurons in the output layer are linear. The weight between the input and the output layer is estimated using recursive algorithm. The experimental studies on the various benchmark data sets show that the Mc-FCFLN outperforms FCFLN classifier. The performance study in comparison with FCFLN clearly indicates that the proposed classifier has a better classification ability. ManjeevanSeera et al. in 2015 [19]has been described a modified FMM network for data clustering. Before evaluating the usefulness of MFMM, a number of clustering methods are first reviewed. Useful modifications pertaining to FMM an efficient clustering method have been proposed. These include procedures for computing the cluster centroids. A number of benchmark data sets have been used to evaluate the evolution patterns of the cluster structures of MFMM, and to compare the MFMM performances with those reported in the literature. The CCC results of MFMM obtained from the benchmark studies are better than those from other existing clustering methods. Min-Yuan Cheng et al. in 2014 [23]constructed using simulation data is a major limitation of EMARS. EMARS thus should be tested more widely using actual datasets and other real problems in the field of building energy performance. Nevertheless, the collecting and processing data newly actual datasets are of great efforts and time consuming. They would like to consider this to be promising future research directions. Jujie Wang et al. in 2014 [24]proposed a novel EMD–ENN approach, which combines empirical mode decomposition (EMD) and the Elman neural network (ENN), is to forecast wind speed. First, the original wind speed datasets are decomposed into a collection of IMFs and a residue by EMD, which are relatively stationary sub-series and can be readily modeled. Second, both the IMF components and the residue are used to establish the corresponding ENN models. Anirudh S. Shekhawat in 2014 [7]gave a paper that stated about wind speed forecasting methods implementing two back propagation algorithms both of which use the LM algorithm. Those two methods are NAR NAR (Nonlinear Auto Regression) and NARX (Nonlinear

Auto Regression with Exogenous input). After implementation, the author concluded that NARX was more effective than NAR. Both the pre processing methods delivered good performance using the LM algorithm.Zibo Dong et al. in 2013 [33]proposed ESSS model. Compared with other popular statistical time series models like ARIMA, LES, SES and RW, the ESSS model has better forecasting accuracy for the forecasting horizon from 5 to 20 min. The forecasting interval produced by the ESSS model can achieve 90% accuracy. Moreover, our novel formulation of Fourier trend model also outperforms other trend models.

**3.Objective:** The principle aim of this proposed study of work is to find the capacity of the artificial neural networks to figure out the most result oriented weights to gauge power generated from forecasting of solar irradiation. The records of past collection of data are used for this purpose. The most efficient and fruitful model is to found that shall provide optimum results. The outcomes form the effective system of models are matched and compared with liner systems of model to evaluate the effectiveness of the Artificial Neural Networks to acquire the non linearity traits of the input domain values.

## 3. Methodology:

Artificial Neural Networks (ANN) is the term used for systems which try to work the way human brain works. Means system try to perform certain task the way humans do.Normally computers do any work the way it is instructed in the form of code, but it does not have the capability of completing works which it was never taught of. But if we consider a human brain, it has self-learning capability which makes it perform much process which it has been neither performed nor taught. So, ANN basically tries to inherit this capability of human brain to self-train itself for tasks which are never been performed by it that too very efficiently. Human brain's structure consists of neurons which are interconnected with each other and there by forming a very large network which is well connected thereby helps in performing very complex task like voice and image recognition very easily. The same task when performed using normal computer won't give accurate result. Hence ANN mimics neurons structure of human brain to discover link between input and targets. Neurons have this ability to save previous experimental data.

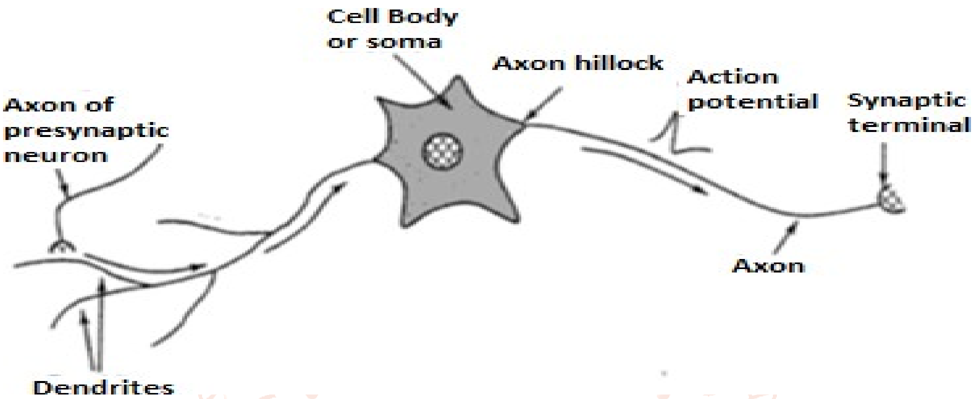


**Fig 1 Biological Model of Neuron**

The speed of human brain is several thousand time faster than traditional computer because in brain unlike traditional computer as whole information is not passed from neuron to neuron they are rather encoded in the neuron network. This is reason why neural network is also named as connectionism.

The dendrites are the branches that are linked to the cell body and stretched in space around the cell body to receive signals from neighboring neurons. The axon works as a transmitter of the neuron. It sends signals to neighboring neurons. The synapse or synaptic terminal are the connection between the axon of one neuron and the dendrites of neighboring neutron, which is the communication link in between the two neurons.

Electrochemical signals are communicated from the synapse. When the total signal received by a neuron is more than the synapse threshold, it causes the neuron to fire i.e., send an electrochemical signal to neighboring neurons. It is assumed that the change in the strength of the synaptic connection is the basis of human memory [20]. This change is developed in ANN in the form of weights between neurons.

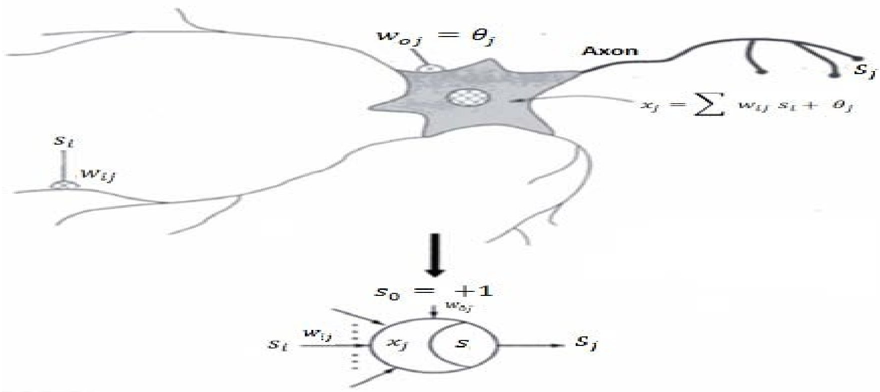


**Fig 2 Mathematical equivalent of Neuron**

In order to perform any type of action in our body, different parts of the body (sense organs) send signals which travel through other parts and reach the brain neuron's where the neuron processes it and generates the required output signal. It should be

noted though that the output of a neuron may also be fed to another neuron. A collection of such neurons is called a neural network. The transformation of the biological model of neuron into a mathematical model is shown in the figure 2. "x" are different inputs which are weighted by a weight corresponding to a path that the signal travels. The neuron is then expected to add an effect in the form of an activation function and the complete signal then goes through a transformation S which produces the output of the neural network. Consider a signal $s_1$ travelling through a path $p_1$ from dendrites with weight $w_1$to the neuron. Then the value of signal reaching the neuron will be $s_1. w_1$.If there are "n" such signals travelling through n different paths with weights ranging from $w_1$ to $w_n$and the neuron has an internal firing threshold value of $\theta_n$, then the total activation function of the neuron is given by:

$$Y = \sum_{i=1}^{n} X_i . W_i + \theta_{ii} \quad (1)$$

Here $X_i$ represents the signals arriving through various paths, $W_i$ represents the weight corresponding to the various paths and θ is the bias. The entire mathematical model of the neuron or the neural network can be visualized pictorially or the pictorial model can be mathematically modeled. The design of the neural network can be modeled mathematically and the more complex the neural design, more is the complexity of the tasks that can be accomplished by the neural network. The above concept can be visualized by the following diagram:

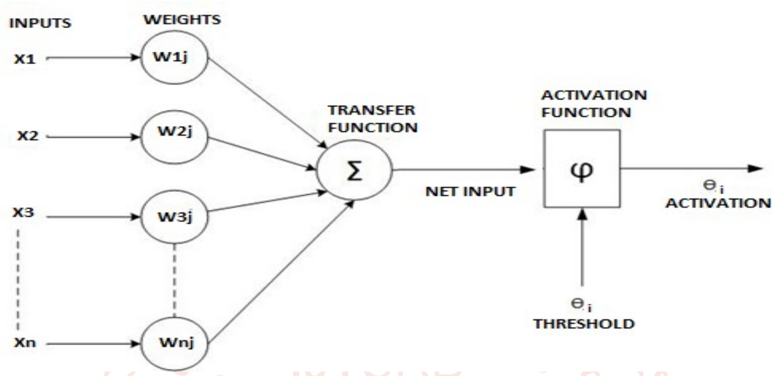


**Fig 3 The mathematical formulation of the neural model**

The soul of the above model lies in the fact that the system so developed tries to mimic the working of human brain in terms of the following:
1. It works in a complex parallel computation manner
2. High speed of performance due to the parallel architecture.

It learning and adapt according to the modified link weights.

Work on ANN has been inspired right from its inception by the acknowledgement that the human brain computes in an entirely different way from the conventional digital computer.

ANN has an astonishing ability to find a relationship between completely non-linear data's which can be implemented successfully to detect trends and thus find the pattern followed by our targets which is impossible for human brains to notice.

ANN poses great ability to train itself based on the data provided to it for initial training. It has the tendency of self-organization during learning period and it can perform during real time operation.

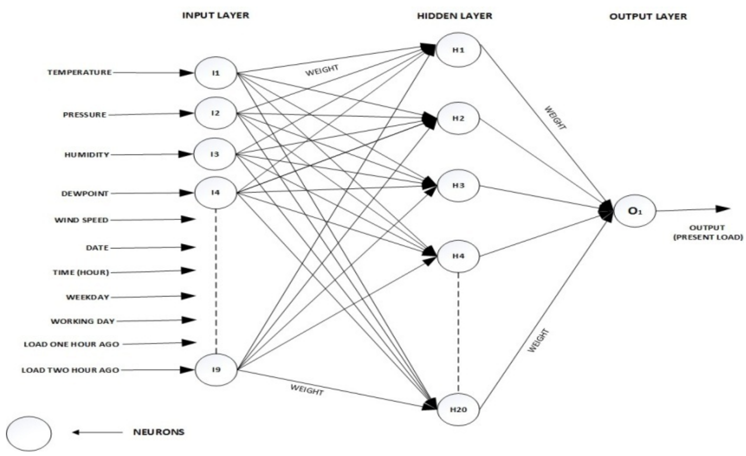


**Fig 4 The mathematical formulation of the neural model**

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Figure 4.shows the working ANN model implemented for present study. To the neurons of the input layer of this network, input signals are fed. This input layers neurons are linked to all the neurons of hidden layer. All these links has some associated weights, whose value depends upon input signal's state. Our aim is to find the optimum values of these weights. The activation function of hidden layer neurons is the main factor in deciding values of weights. Hidden layers neurons are further connected to output layer neurons. The weights of this connection between hidden and output layer is also need to be optimized with prior weights.

## 4. Results And Discussions:

The results are based on the performance metrics utiized in the proposed work.Respective performance analysis and plots and graphs of results have also been illustrated to provide a clear picture. The best state that gives the optimim result has also been stated.

The tool Matrix Laboratory (MATLAB R2017a) has been used to carry out this proposed work based using the Levenberg Marquardt back propagation algorithm. The following section presents and exemplifies the results.

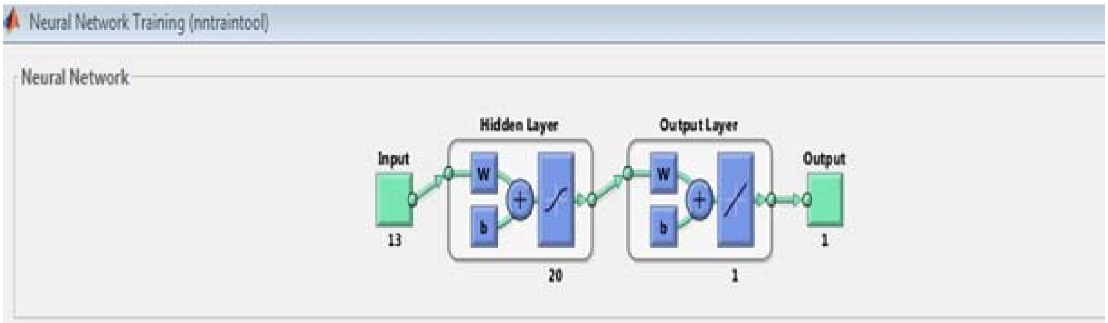


**Figure 5 Visualization of Designed Neural Network for LM Training.**

In this image, the neural network system can be observed that is set on the LM algorithm. Various layers can be seen to be connected and related. W is the value for branch weight for connection and bias value is denoted by b. Weights is further classified as Input weights: weights among the input layer and hidden layer and Layer Weights: that are the weights situated between concealed layer and neurons of output layer.

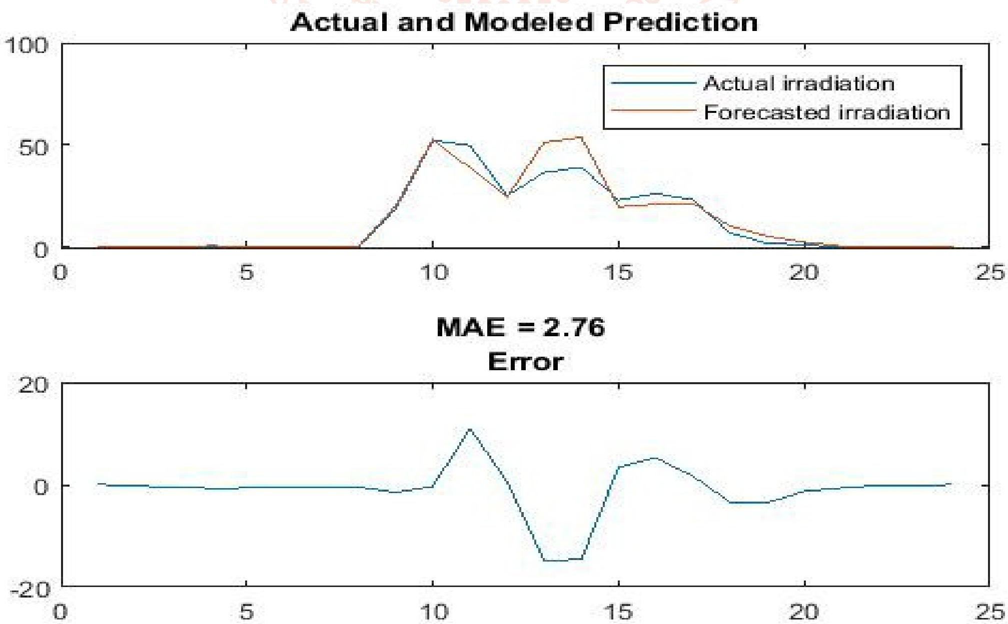


**Figure 6 Comparison between the predicted and actual solar irradiation employing the proposed model using LM training.**

The figures given above show the prediction system model for solar irradiation. A combined and superimposed analysis of actual and predicted solar irradiation has been shown in figure 6. It can be seen that the proposed system achieves a Mean Absolute Percentage Error (MAPE) or MAE% of just 2.76%. Figure 6.gives the plot diagram of performance. This is depicted as the function of performance and measure of repetitions. After 30 epochs the optimally best performance is found. The

validating process entails supervision for validity and scope of subsequent increase in performance. If no such further possibility of betterment is conducive, it is not trained anymore and stopped. The outcomes are put forth for comparative analysis.

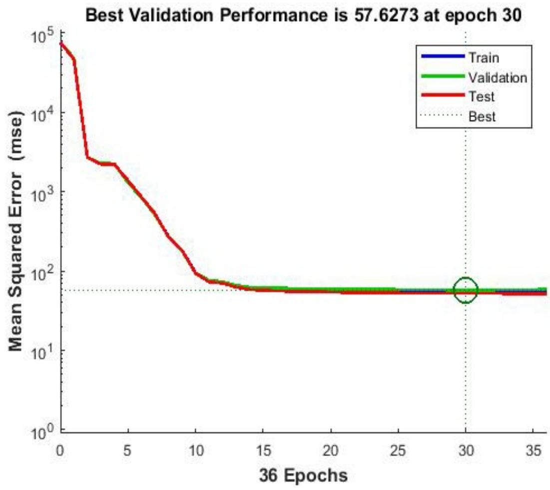


**Figure 7 Computed MSE value using the proposed LM trained Neural Network**

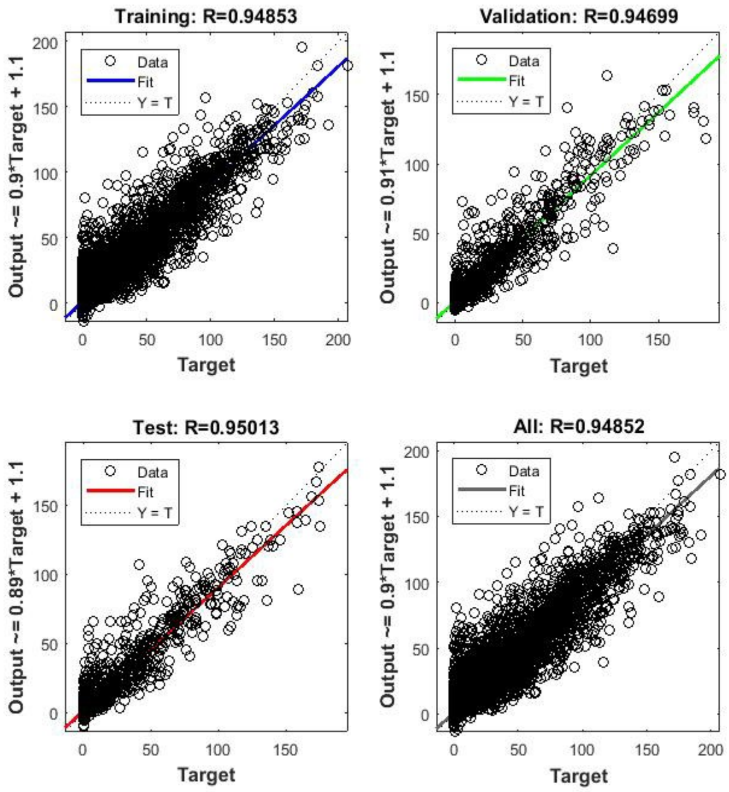


**Figure 8 Regression plot during training, testing & validation for Proposed for Bayesian LM training algorithm**

The measure of correlation amongst the output metrics are done by the R which is the Regression value. When R is 1, it signifies a relation that is quite close and R as 0 conveys the relation to be loose and random. It can be seen from figure 5.4 that the overall regression of the proposed system is 0.948 which is pretty close to 1, thereby rendering validation for the high accuracy achieved. The captured image of the training procedure has been shown as the neural network screen shot from MATLAB implementation in the Figure. 8. As follows-

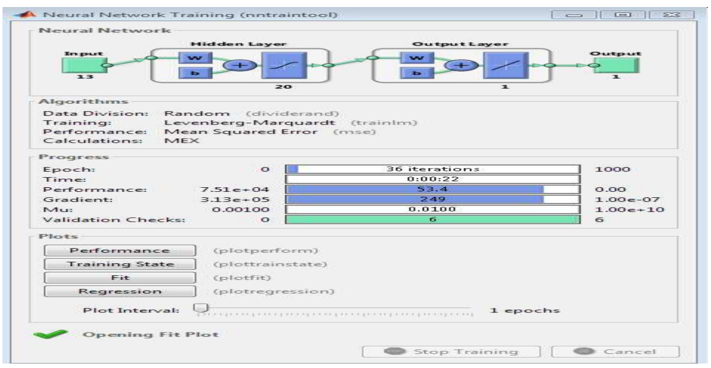


**Figure 9 The training phase using the NN Tool**

The following points can be noted about the designed ANN architecture.

1) There are 20 neurons in the hidden layer. The number of neurons in the hidden layer decides the efficacy with which the neural network can analyze a problem. The more the number of neurons in the hidden layer, more is the system's computational caliber but the system complexity increases.

The training algorithm used in the proposed system is the Levenberg-Marquardt back propagation algorithm. It is both stable and fast thereby rendering accuracy and low time complexity to the proposed system. The number of validation checks is 6 which indicates the fact that the ANN architecture checks for any changes in the state of errors for 6 times before it ends training and starts testing.

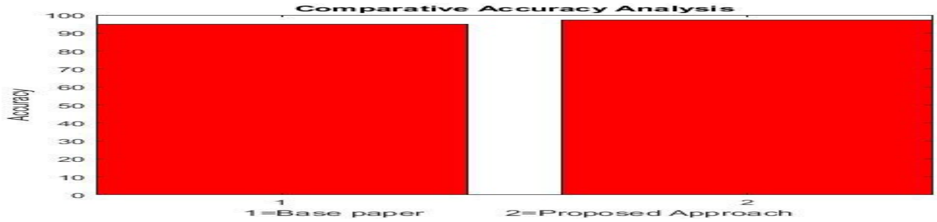


**Figure 10 MAPE comparison with base paper**

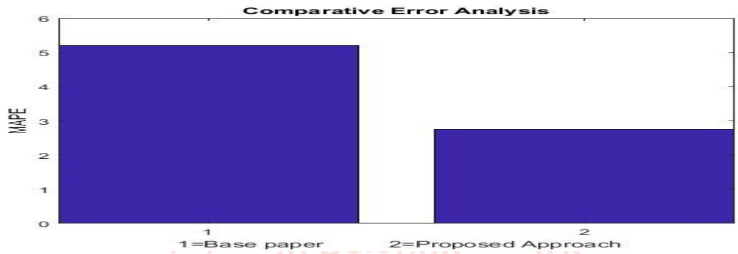


**Figure 11 Accuracy comparison with base paper**

## 5. Conclusion:

So in the given work, it has been tried to predict solar irradiation using Back Propagation in Artificial Neural Networks. The Levenberg-Marquardt back propagation algorithm has been used for the proposed approach. The number of neurons taken for the design is twenty though it can be varied. The proposed system attains an accuracy of 97.84% and a mean absolute percentage error (MAPE) of 2.76%. The following additional concluding points can be inferred.

1) Here the data collected in quantity that can also be termed as mining of data shows exhaustive trait.

2) The Levenberg-Marquardt (LM) Algorithm has also been used to test and train the ANN. This happens to be an efficient method that offers stable forecasting and also converges fast.

It has been shown that the proposed technique achieves lesser errors and higher accuracy compared to contemporary techniques. The low error or high accuracy values can be validated using the regression of the proposed system which is 0.948 (approx).

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